WHO REQUESTS GENERIC DRUGS FROM THEIR DOCTOR?

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Toan Minh Luong

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Abstract

Rising faster than either wages or the cost of living, prescription drug expenditures present a significant burden on the economic well-being of patients in the United States. To curb such financial pressure on government healthcare programs, patients are encouraged to consume more generic medications that can be as much as 85 percent cheaper than their brand-name counterparts. Using the 2013 Medicare Current Beneficiary Survey dataset, this study explores the likelihood that Medicare beneficiaries requested generics from their primary doctors. The logistic regression model includes variables related to beneficiaries' demographics, health conditions, insurance coverages, doctor-patient relationships, and cost-awareness. The final results align with those of previous studies by suggesting that non-Hispanic black beneficiaries older than 65 and those with higher education were more likely to request generics compared with those of other demographic groups. Other interesting findings show that beneficiaries who had experiences with drug samples, were satisfied with their drug coverage, and were cost-sensitive when shopping for medications tended to request generics more frequently. These conclusions have tremendous implications for policymakers, insurance companies, and generic manufacturers to provide educational programs, advertising campaigns, and financial incentives that promote low-cost generics usage and can save patients billions of dollars in medication expenditures.

KEYWORDS: (Healthcare, Prescription Drug, Generic, Brand, Medicare)
JEL CODES: (I12, I13)

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Introduction

Expected to surpass $4.6 trillion and $610 billion by 2020 respectively, healthcare costs and medication expenditures present a significant barrier to the economic well-being of patients in the United States (Riaz & Krasuski, 2016). Far exceeded the general inflation rate of 0.1%, spending on prescription drugs rose 12% to a record $425 billion in 2015 due to the exorbitant prices of several breakthrough medicines for cancer and hepatitis C (Cortez, 2016). Such upward trend of pharmaceutical costs negatively affects close to 75% of American seniors, who rely on daily prescription medications, and the Medicare program, which provides them medical access and drug coverage (Barnett, 2005; Jones, Carrier, Silver, & Kantarjian, 2016). To increase affordability, the U.S. Congress enacted the Hatch-Waxman Act,[1] which encourages manufacturers to produce generic versions of brand-name medications that are equivalent in safety and effectiveness. The introduction of generic drugs consequently reduced U.S. healthcare spending by $1.46 trillion over the last decade (AAM, 2016). Understanding patients' preferences for generic medications thus becomes an important priority for policymakers, insurance companies, and pharmaceutical firms to promote generic drug usage and reap the enormous cost-saving benefits.

Pharmaceutical innovations are both a blessing and a curse that lead to the high annual drug expenditures of Medicare beneficiaries. According to Express Scripts (2015), more than 7,000 potential drugs are in development to treat oncology, neurologic disorders, and infectious diseases. Yet once approved by the U.S. FDA,[2] the

[1] The U.S. Congress passed the Drug Price Competition and Patent Term Restoration Act, typically referred as the Hatch-Waxman Act in 1984.
[2] Food and Drug Administration.

manufacturers can reserve the chemical patent rights, monopolize the drug supplies, and keep their competitors out of the market (Kodjak, 2016). The U.S. legislative structure provides drug manufacturers a median length of 12.5 years of post-approval market exclusivity for widely-used drugs and 14.5 years of that for highly innovative and first-in-class drugs (Wang, Liu, & Kesselheim, 2015). The lack of price-based competition thus contributes to the inflated prices of certain branded medications. Between 2008 and 2015, the prices of branded medications increased 164% on average that was far in excess of the consumer price index of 12% (FDA, 2016). For instance, Novartis raised the market price of Gleevec from $25.50 to $112.37 per tablet within 10 years (Express Scripts, 2015). The list goes on with the shocking price hikes of Daraprim by Turing Pharmaceuticals, Glumetza by Valeant Pharmaceuticals, and most recently, EpiPen by Mylan N.V. Medicare beneficiaries paid as much as $11,538 for the out-of-pocket portion when receiving specialty prescription drugs treating arthritis, cancer, or other complex conditions (Kodjak, 2015).

Low-cost generics help to curb these rising prescription drug costs. By definition, a generic drug refers to a bio-equivalent version of a brand-name small-molecule drug by a different manufacturer (Kesselheim, Avorn, & Sarpatwari, 2016). Because of heavy competition among generic manufacturers, prices of generic drugs can be as low as 2 to 10% of equivalent brand-name drugs (FDA, 2015). An analysis of calcium leucorovinm, cytarabine, vancomycin, clindamycin, and methyldopa drugs also shows an average price decline of 14% just one year after initial generic entries (Grabowski & Vernon, 1992). As a result, generic drug usage indeed brings a significant reduction in overall medical expenditure for individuals, employers, and health insurance companies. The estimated

medical savings was $227 billion in 2015 (AMA, 2016). The affordability of generics also leads to a higher adherence to prescribed therapies and better medical outcomes for patients.

Actively asking doctors to prescribe generic instead of brand-name drugs is one of the most efficient approaches to manage treatment costs. Medicare beneficiaries who were most cost-sensitive and communicated their preferences for generics to their primary doctors each saved an annual average of $1,737 (AAM, 2016; Frist, 2005). However, previous studies suggest that several barriers related to patients' demographics, health conditions, drug coverages, and doctor-patient relationships hinder their tendencies to request generics. For example, patients often face difficulties navigating their drug options and out-of-pocket expenses due to the substantial variability and complexity of formularies and insurance cost-sharing settings (Kohl & Shrank, 2007). Previous studies by Shrank, Cox, Fischer, Mehta, and Choudhry (2009) and Alexander, Casalino, Tseng, McFadden, and Meltzer (2004) indicate infrequent and significantly weak communication between patients and their doctors. Consequently, more than 52% of respondents reported that they never or seldom discussed the available and more affordable generics options with their doctors.

This study seeks to validate the characteristics contributing to the likelihood of Medicare beneficiaries requesting generic medications from their primary doctors in 2013. The results will provide Medicare sponsors and policymakers valuable insights into the beneficiaries' preference for generics. Educational efforts about the financial and clinical benefits of generic medications can be targeted to certain demographics who tend to distrust generics. Private insurers can also introduce drug tiers, step therapies, and

other advisory programs to incentivize their members to request generics more frequently.

The next section provides a review of relevant literature, followed by a detailed analysis of the factors contributing to patients' willingness to request generic drugs. Section 2 outlines the theory and econometric model that will be applied to the data described in Section 3. Section 4 summarizes the findings, error corrections, and propose several model improvements. Section 5 presents the policy implications and future research avenues in detail.

Literature Review

Based on public surveys, interviews, and pharmacy claims, previous studies successfully outline different perceptions of cost-saving benefit, efficacy, and risk of generic drugs held by doctors and patients. The results also provide insights on which patients' socio-economic characteristics indicate a higher or lower preference to generic medications. Yet, few studies directly analyze the likelihood that an individual patient requests generic drugs from their primary doctor.

Doctors' Perceptions of Generic Medications

Shrank et al. (2011) conducted a cross-sectional survey analysis of primary care physicians and specialists based on 506 eligible responses. Almost 50% of these medical personnel reported feeling negatively about the quality of generic drugs and preferred not using them as first-line medications for themselves or their family. In addition, physicians over 55 years old were 3.3 times more likely to distrust generics than younger ones. Most researchers agreed that doctors do not assume the responsibility to make medical treatments more affordable by prescribing low-cost generic drugs. Previous experiences, personal habits, and financial incentives from drug manufacturers could motivate physicians to prescribe expensive brand-name medications. Such action presents a potential barrier to promote familiarity with low-cost equivalent generics among the general patients.

Patients' Perceptions of Generic Medications

Demographics. Shrank et al. (2009) surveyed 2,500 commercially insured beneficiaries of a national Pharmacy Benefits Manager. Out of 1,047 eligible responses, more than 70% of respondents appreciated the cost-saving benefits of generic drugs, however only 37.6% accepted them as alternative treatments. Other studies also reveal the demographics who had a significantly higher or lower likelihood to consume generics. Females and those earning more than $100,000 a year indicate a stronger preference for generics. Yet, sicker, poorer, and older patients express serious concerns about the safety and efficacy of generics.

Based on the two-year pharmacy claims of Anthem Blue Cross and Blue Shield, Shrank et al. (2007) discovered that residents in poor ZIP codes, who were least likely to afford expensive treatments, were over 25% more likely to receive branded medications compared with other demographics. On the other hand, elderly patients over 55 years old, who had more experience and knowledge about purchasing medications, were over 7.5 times more likely to switch to generic drugs than young patients. Keenum, Devoe, Chisolm, and Wallace (2012) found similar results in the population of women of child-bearing age who enrolled in the U.S. TennCare program. With regards to race/ethnicity, Iosifescu, Halm, McGinn, Siu, and Federman (2006) found that negative perceptions of generics significantly associated with patients of non-white race and with inadequate health literacy. One of the reasons was that African-American patients reported lower trust and satisfaction with their doctors' communication, which hindered their access and familiarity with low-cost generic drugs (Cooper-Patrick et al., 1999; Doescher, Saver, Franks, & Fiscella, 2000).

***Health Conditions*.** Ganther and Kreling (2000) concluded that patients in Wisconsin perceived the risks of consuming generic drugs differently and based on existing medical conditions. Evidently, 53.8% of these patients found that generic medicines were riskier than their brand-name counterparts when used to treat heart-related problems. Yet, only 14.2% expressed similar concerns with respect to generic medications that treat coughs and other minor conditions. According to Figueiras, Marcelino, and Cortes (2008), with regards to several popular health conditions such as flu, asthma, and angina pectoris, patient with more severe conditions tended to distrust generic medicines. In another study that was based on 174 interviews with Norwegian patients, 29% of the interviewees were anxious when prescribed a generic version of an antihypertensive drug (Håkonsen, Eilertsen, Borge, & Toverud, 2009). Other studies of patients in European countries also show a variation in the preferences for generic medications of patients with different medical conditions. In a questionnaire-based study in Finland by Halme, Linden, and Kääriä (2009), 33% of the patients considered brand and advice from healthcare professionals most importantly when selecting an over-the-counter analgesic for headache. Among the renal transplant patients in the U.K., 84% of the respondents were unsure of generics' equivalency and quality compared with their brand-name counterparts (Al Ameri, Whittaker, Tucker, & Johnston, 2011).

***Insurance Coverage and Cost-sharing Setting*.** The presence of insurance coverage allows patients more medication choices and effectively lowers their share of drug prices. Such provision of choice might lead to expensive brand-name treatments (Zweifel & Breyer, 1997). In contrast, with regards to indemnity-insured or uninsured patients who have to pay the full retail prices of their prescription drugs, physicians and

pharmacists are understandably more willing to prescribe them the low-cost generic versions (Mott & Kreling, 1998). Furthermore, the type of coverage and cost-sharing setting could significantly influence generic drug usage. Prescriptions covered by Medicaid were 4.57 times more likely to be generically substituted relative to those coved by private third parties, because Medicaid sponsors only reimburse pharmacies for prescribed generics (Mott & Cline, 2002). According to another analysis of the Medicare Part D senior enrollees in 2009 by Tan, Men, and Donohue (2014), large differentials in brand-generic cost-sharing setting could result in a higher likelihood of enrollees consuming generic drugs. Sensitivity to out-of-pocket expenses, which often associates with enrollees in high-premium plans, could encourage enrollees to consume generics more frequently. For examples, patients in plans with 3 or 4 tiers of copayment requirements were almost 4 times more likely to switch to generics compared with others (Shrank et al., 2007).

Communication between Doctors and Patients. Finally, the communication between patients and their primary doctors has an important role in reducing medication expenditures and promoting generic drug usage. Based on a telephone survey from a primary care physician-patient panel in 2003, Shrank et al. (2006) discovered that approximately 38% of patients reported having no knowledge of their out-of-pocket requirements, and over 68% never discussed any financial concern with their primary physicians. These patients could be vulnerable to the excessive financial burden of copay obligations, which might adversely affect their medication adherence and treatment outcome. Alexander et al. (2004) also showcased evidence of the poor-quality and infrequent communication between physicians and their patients about their out-of-

pocket medication expenditures. The authors outlined a number of possible reasons including personal discomfort, insufficient time, absence of viable solutions offered by the physicians, and fear of compromised quality. Notably, elderly Hispanic patients interacted with their physicians less frequently due to various cultural, linguistic, and cognitive barriers (Shrank et al., 2006).

In summary, previous studies confirm the important determinants of patients' medication preferences and willingness to consume generic drugs. The factors include patients' demographics, health conditions, insurance coverages, cost-sharing settings, and communications with their primary doctors. However, most studies rely on self-administered interviews, mailed questionnaires, surveys, and pharmacy claims, which results in a significant variability in outcome measure, key dependent, and controlled variables. Most authors acknowledge similar limitations of sample bias, size limit, low rate of participation, and missing indicators in their research. Such drawbacks hinder the generalization of their results to the studied population.

This section details the literature related to the perceptions of generic medications held by different stakeholders. The next section explains the empirical model that estimates the likelihood of patients requesting generics from their primary doctors. Previous studies and successful methodologies will guide the construction of the base model and additional modifications that fit the research objective of further understanding patients' preferences for generic drugs.

Theory

Relevant literature show that generic medications provide various financial and clinical benefits that improve patients' treatment outcomes and reduce their medical expenditures. However, most studies emphasize on the role of physicians and pharmacists who can introduce generics to their patients. Existing literature thus lacks an in-depth analysis of patients' tendencies to actively request generics from their primary doctors. This study attempts to model such tendency of Medicare beneficiaries who mostly are seniors older than 65 years of age and likely to consume daily prescription medications.

Base Model

Mott and Cline (2002) constructed a regression model that measures the likelihood that an eligible prescription was prescribed as generic. Equation 3.1 shows the relationship equation.

$$Prob(g_{kl} = 1) = Prob(\delta + \phi W_{kl} + \tau_l + \upsilon_{kl}), \quad (3.1)$$

$Prob(g_{kl} = 1)$ denotes the probability that the pharmacist endorsed an eligible generic prescription. W_{kl} refers to a vector of independent variables related to prescription drug coverage types, patient demographics, and characteristics of prescribed medications. The error terms τ_l and υ_{kl} account for unobservable random errors of the generic substitutability and any personal incentive to prescribe generics of the pharmacist. This model sets the foundation to control for different predictors of generic drug usage and accounts for unobservable regression errors. Further modifications to the base model are needed to estimate the likelihood of patients actively requesting generics from their primary doctors.

Modifications

The base model considers age, gender, and race as the primary components of patient demographics who tend to consume generics. According to Shrank et al. (2007) and Federman et al. (2006), income and education level are also important predictors of generic drug usage because wealthy and well-educated patients receive more public information about the equivalency and other cost-saving benefits of generic medications. Moreover, the fact that the patient lives in a metropolitan or non-metropolitan area also determines their tendency to request generics. Metropolitan-residing patients have better access to generic medications because more drug stores, marketing activities, and drug samples are available and easily accessed in urban areas.

Most previous studies agree that patients with complex and severe medical conditions tend to be more risk-averse and anxious about consuming generic medications. As a result, indicators of the patient's health status are relevant to the empirical model and account for their risk perceptions of generics. Examples of such indicators can include the total number of chronic diseases or the annual volume of medications consumed by the patient (Isoifescu et al., 2008).

In the base model, Mott and Cline (2002) incorporate various drug coverage types to reflect their differences in out-of-pocket expenditures, formularies, and other administrative mechanisms. Shown in the literature review, the presence of drug coverage, in addition to its formulary and cost-sharing setting, significantly influences patients' tendencies to switch to generics. More importantly, out-of-pocket spending measures the financial burden and directly incentivizes patients to request generics from their primary doctors. The empirical model thus includes indicators that reflect an

individual patient's satisfaction with their insurance plan, out-of-pocket spending, formulary, and access to local pharmacies.

Indicators related to doctor-patient relationship are also significant additions to the base model. Ideally, doctors communicate all available treatment options and create a comfortable environment for their patients who can freely ask questions or express financial concerns. Such a relationship allows doctors to introduce generics to their patients and influence their tendencies to request similar generic medications subsequently (Alexander et al., 2004; Shrank et al., 2006). The frequency that patients ask for or receive generic drug samples from doctors also determines their preferences for generics in the future. Drug manufacturers often distribute free drug samples with the purpose of influencing doctors' prescription writing habits and maximizing profits (Lahey, 2014). Because receiving drug samples and other gifts from pharmaceutical companies endangers their reputation and reduces their patients' trusts, such risks permit doctors to only prescribe samples to themselves, their families, and regular patients (Jastifer & Roberts, 2009; Green et al., 2012; Westfall, McCabe, & Nicholas, 1997).

Empirical Model

The empirical model used in this study is as following:

$$Prob(\boldsymbol{G_i} = 1)$$

$$= Prob(\beta_0 + \beta_1 * \boldsymbol{\mathcal{D}_i} + \beta_2 * \boldsymbol{\mathcal{H}_i} + \beta_3 * \boldsymbol{\mathcal{R}_i} + \beta_4 * \boldsymbol{C_i} + \beta_5 * \boldsymbol{\mathcal{A}_i} + \varepsilon_i)$$

where $Prob(\boldsymbol{G_i} = 1)$ is the probability of a patient i requesting generics from their primary doctor, as predicted by patient-level data of:

- β_0, representing the bias term,
- $\boldsymbol{\mathcal{D}_i}$, representing the matrix of variables capturing the patient i's demographics such as age, gender, race, income, marriage status, education level, and whether they live in a metropolitan residence,
- $\boldsymbol{\mathcal{H}_i}$, representing the matrix of variables capturing the general health status self-reported by the patient i,
- $\boldsymbol{\mathcal{R}_i}$, representing the matrix of variables capturing the relationship quality between the patient i and their primary doctor,
- $\boldsymbol{\mathcal{C}_i}$, representing the matrix of variables capturing the patient i's satisfaction with their drug coverage,
- $\boldsymbol{\mathcal{A}_i}$, representing the matrix of variables capturing the patient i's cost-awareness when obtaining prescribed medicines, and
- ε_i, representing unobservable characteristics of the patient i with regards to requesting generic medications.

This section details the empirical model that incorporates insights from relevant literature and improves upon the base model by Mott and Cline (2002). By adding variables characterizing the patients' demographics, health conditions, doctor-patient relationships, and satisfactions with drug coverages, the model provides an empirical estimation of the patients' tendencies to request generic medications. The subsequent section describes all listed variables in the context of the 2013 Medicare Current Beneficiary Survey dataset.

Data

This section discusses the Medicare Current Beneficiary Survey (MCBS) as the primary data source, followed by its design and application in the proposed model. The selection and consolidation of dependent and independent variables will be described in detail and supported by relevant summary statistics. Finally, this section concludes with a discussion of MCBS's key advantages and limitations in establishing patients' tendencies to request generic medications.

Dataset

Conducted by the Centers for Medicare and Medicaid Services (CMS), MCBS is a continuous, in-person, and representative national sample of the Medicare population in the U.S, the District of Columbia and Puerto Rico. Having existed for more than 20 years and encompassing more than one million interviews, MCBS is an invaluable source of information for administering the Medicare program, estimating its expenditures, and understanding its impacts on the Medicare beneficiaries (CMS, 2016). This study uses the 2013 MCBS Access To Care (ATC) dataset that is publicly available. Such availability is part of the CMS Office of Minority Health's recent initiative to promote research on Medicare effectiveness and eliminate health disparities for minorities.

According to the CMS User Guide (2016), the 2013 MCBS ATC dataset includes 13,924 survey respondents whose identities and health information are de-identified and protected. Based on the topics present in the survey questionnaire, the dataset provides insights into each beneficiary's demographic, health status, functioning, access to healthcare, insurance status, housing characteristics, and other interview administrative information. The MCBS has a complex design and sampling methodology to ensure that

the dataset is representative of the national Medicare population.[3] The selected interviewees were continuously enrolled in one or both Medicare parts from January 1, 2013 up to and including their interview between September and December of 2013. MCBS sampling methods include stratification, clustering, multiple stages of selection, and disproportionate sampling, in addition to adjustments for survey non-responses. Based on CMS guidelines, "cross-sectional and replicate weights[4] should be declared in advance, in order to account for both differential weighting and correlation among sampled beneficiaries within a cluster". Such process allows the generalization of statistical estimates to the national Medicare population in 2013. Without proper adjustments for survey weights and design procedures,[5] multivariate models' variance estimates are more likely to have downward biases, and significance levels of certain variables can be overstated (CDC, 2011; Wiener, Shen, Sambamoorthi, & Usha, 2016).

[3] Sampling methodology is also representative of the following age groups: under 45, 45 to 64, 65 to 69, 70 to 74, 75 to 79, 80 to 84, and 85 and over.
[4] These are labeled as CS1YRWGT and CS1YR001-100 in the dataset.
[5] CMS provides a model STATA statement to incorporate sample weights prior to analysis, as followed: svyset _n [pweight=cs1yrwgt], brrweight(cs1yr001-cs1yr100) fay(.3) vce(brr) singleunit(missing).

Selection and Consolidation

As detailed in the previous section, the proposed model in this study focuses on Medicare beneficiaries who had any form of prescription drug coverage during their interview period. Such coverage can be obtained through public or private insurance plans, Medicare Part D, and Medicare Advantage. Based on the MCBS Codebook (CMS, 2016), researchers can apply a filter to variables that indicate beneficiaries' satisfactions with their drug coverage, formulary, and out-of-pocket cost, in order to select respondents who had any form of drug coverage in 2013. This process eliminates 1581 (11.4%) entries.

Out of 356 variables in the 2013 MCBS ATC dataset, 21 are selected to fit the proposed model. Survey entries with missing, "refused" and "don't know" responses are universally coded as blank, -7, and -8 respectively. Respondents with any of these three characteristics are excluded for all selected variables (Henning-Smith, Casey, & Moscovice, 2016). The final sample size is 10,048 survey entries with a weighted population estimate of 33,887,811 beneficiaries nationwide.

Dependent Variable

Based on the model's equation, the dependent variable in this study is $\boldsymbol{Prob}(\boldsymbol{G_i = 1})$, which reflects the probability of a Medicare patient i asking their doctor for generic instead of brand-name medications. In the 2013 MCBS ATC dataset, the variable coded as ACC_GENERRX captures the logit score $\boldsymbol{G_i}$ precisely. As calculated in Table 3.1, 55.19% of the respondents reported that they never requested generics. The remaining 44.81% sometimes or often asked their doctors to prescribe generics.

Table 3.1

Description of Dependent Variable

MCBS Original Code	Survey Question[6]	Responses	Weighted Proportion
ACC_GENERRX	Have you often, sometimes, or never asked for generics instead of brand name drugs?	1: Often 2: Sometimes 3: Never	33.69 % 11.12 % 55.19 %

Source. 2013 MCBS ATC Codebook (CMS, 2016).

According to Kesselheim et al. (2016), the authors dichotomize between "Never" and any other answers when processing a tangentially similar survey question of "How often patients reported asking their primary doctors to prescribe a brand-name rather than a generic drug in the last year?". Hence, derived from the original ACC_GENERRX variable, ASK_GENERIC is generated by coding zero for "Never" and one for both "Often" and "Sometimes" responses. Table 3.2 displays the post-converted number of observations, weighted count, proportion, and other summary statistics for the binary dependent variable ASK_GENERIC.

[6] This question is rephrased from the MCBS ATC Codebook (CMS, 2016).

Table 3.2

Summary Statistics of Dependent Variable

Variable Label	Code	Observation Frequency	Weighted Count	Weighted Proportion	CV	DEFF
ASK_GENERIC	1: Yes	4396	15,185,989	44.81%	1.9	4.1
	0: No	5652	18,701,722	55.19%	1.8	2.9

Source. Author's Calculations.

This paragraph explains the summary statistics reported for the dependent and independent variables from Table 3.2 to Table 3.7. The results are obtained in STATA 13.1 (StataCorp LP, College Station TX). Each value in the "Observation" column notes the number of survey respondents for each answer choice. The "Weighted Count" and "Weighted Proportion" columns report the population estimates and generalized proportions with the same answer choice after accounted for sampling weights. Coefficient of variation (CV) refers to the uncertainty percentage associated with each population estimate. Design effect (DEFF) measures the loss of effectiveness due to cluster sampling. For example, "a DEFF of 3 shows that one-third as many sample cases would be needed to measure the given statistic if simple random sampling was used". For a well-designed study, DEFF usually ranges from 1 to 3 (Shackman, 2001). Both CV and DEFF indicate the extent to which sampling errors affect statistical tests and other methods of inference. In Table 3.2, ASK_GENERIC has a more balanced distribution between two converted responses. The 18.7 million Medicare beneficiaries (44.81%) are now assigned to "1: Yes" response. All other statistics are in the normal range.

Independent Variables

Independent variables are selected in accordance to the five explanatory matrices $\boldsymbol{\mathcal{D}_i}$, $\boldsymbol{\mathcal{H}_i}$, $\boldsymbol{\mathcal{R}_i}$, $\boldsymbol{\mathcal{C}_i}$ and $\boldsymbol{\mathcal{A}_i}$ in the proposed model. Following the CMS labeling conventions, all variables are re-labeled in order to succinctly capture the survey questions and reflect the concepts shown in the literature review. All 21 independent variables are categorical and dummy-coded prior to any regression analyses. For example, a categorical variable with k categories is transformed into $k - 1$ separate dummy variables with two universal levels: 0 and 1 (Stockburger, n.d.). To avoid perfect collinearity, a reference category is specified for each predictor and its associated dummy variable is excluded from further analyses. This study selects reference categories that represent negative or trivial responses such as "No", "No experience", and "Never". For demographic-related variables, the reference categories are those of under-represented Medicare populations that do not support our hypotheses. All reference categories are denoted by an asterisk (*) from Table 3.3 to Table 3.7. In addition, Table 6.1 in the Appendix details the original MCBS codes and survey questions that correspond to each independent variable.

Demographic Characteristics. The $\boldsymbol{\mathcal{D}_i}$ matrix consists of categorical variables that denote each respondent's sex, race/ethnicity, age, income, education level, marriage status, and metropolitan status. Table 3.3 details these variables and responses which are coded numerically in the dataset. Information on race/ethnicity and age are combined in the ETHNICITY_AGE variable that features 14 distinct combinations. The INCOME variable divides all respondents into two income groups that earned below and above $25,000. Similarly, the EDUCATION variable defines high-school as the benchmark that divides the surveyed population accordingly.

Table 3.3 also summarizes the key statistics of the demographic variables. The SEX variable shows that more women were in the surveyed population than men (55.76% and 44.24% respectively). For ETHNICITY_AGE, the major ethnicity was non-Hispanic white with 76.2% weighted proportion. CV gradually increases to a maximum of 11 and indicates higher standard errors for minorities' population estimates, because fewer respondents of non-white ethnicities were in the survey. However, CMS indicates that minorities of certain age groups and ethnicities were oversampled to permit statistical analysis on these sub-populations (CMS, 2016). As the result, the DEFF of the ETHNICITY_AGE variable has a smaller range of 0.66 to 3.4. For the INCOME, EDUCATION and MARRIAGE variables, the weighted proportions indicate a larger number of Medicare beneficiaries that earned more than $25,000, attended further than high-school, married, and lived in metropolitan areas.

Table 3.3

Summary Statistics of Demographic Variables $(\boldsymbol{\mathcal{D}_i})$

Variable Label	Category/Response	Observation Frequency	Weighted Proportion	CV	DEFF
SEX	1: Male*	4455	44.24%	1.5	1.8
	2: Female	5593	55.76%	1.1	1.6
INCOME	1: < $25,000*	4570	41.27%	1.6	1.8
	2: >= $25,000	5478	58.73%	1.4	2.8
EDUCATION	1: Less than high school*	2082	18.01%	2.7	1.6
	2: High school or vocational, technical, business	3654	35.41%	2.2	2.6
	3: More than high school	4312	46.58%	1.8	2.8

MARRIAGE	1: Married	5183	55.41%	1.3	2.1
	2: Widowed	5183	21.00%	1.9	0.93
	3: Divorced	1436	15.69%	2.8	1.5
	4: Never married*	1063	7.90%	4.0	1.4
METRO	1: Metro area	7522	77.84%	0.99	3.4
	2: Non-metro area*	2526	22.16%	2.3	1.5
ETHNICTY_ AGE	1: Non-Hispanic White, <65 years	1013	9.78%	0.6	1.4
	2: Non-Hispanic White, 65-74 years	2830	36.61%	1.8	1.9
	3: Non-Hispanic White, 75-84 years	2584	20.71%	1.8	0.83
	4: Non-Hispanic White, 85+ years	1073	8.38%	2.6	0.63
	5: Non-Hispanic Black, <65 years	354	2.82%	5.2	0.78
	6: Non-Hispanic Black, 65-74 years	345	3.64%	5.2	1.0
	7: Non-Hispanic Black, 75-84 years	295	2.19%	5.7	0.73
	8: Non-Hispanic Black, 85+ years	80	0.59%	10.0	0.66
	9: Hispanic, <65 years	249	2.68%	11.0	3.4
	10: Hispanic, 65-74 years	304	3.89%	7.1	2.0
	11: Hispanic, 75+ years	372	2.92%	5.4	0.89
	12: Other, <65 years	135	1.30%	13	2.3
	13: Other, 65-74 years	191	2.59%	8.6	2.0
	14: Other, 75+ years*	223	1.90%	7.2	1.0

Source. 2013 MCBS ATC Codebook (CMS, 2016) and Author's Calculations.

Health Characteristics. The $\mathcal{H}_i$ matrix consists of categorical variables that evaluate a respondent's health status by the time of their MCBS interview. Previous studies establish the significance of medical conditions in patients' risk perceptions of generic medications (Al Ameri, Whittaker, Tucker, & Johnston, 2011; Håkonsen, Eilertsen, Borge, & Toverud, 2009; Halme, Linden, & Kääriä, 2009). In addition, a recent

study by Kesselheim et al. (2016) states that patients with chronic conditions were likely to experience numerous fills and refills of generic drugs. Hence, the HYPERTENSION, DIABETES, and CHOLESTEROL variables are considered in this study, because they flag respondents having any of the three conditions. Furthermore, according Sewell, Andreae, Luke, and Safford (2012), African-American patients in rural Alabama expressed a strong distrust when asked about hypothetical generic cancer medications. Thus, the CANCER variable can precisely flag cancer-bearing Medicare beneficiaries and support the proposed model. Table 3.4 details all health-related variables with their corresponding summary statistics.

Patients with heart diseases, for example angina pectoris, tend to express serious concerns against generic drugs (Figueiras, Marcelino, & Cortes, 2008; Ganther & Kreling, 2000). As the result, the HEART variable is generated and based on the five indicators of myocardial infarction, angina pectoris, congestive heart failure, aortic stenosis, and atrial fibrillation.[7] The number of heart-related diseases experienced by a survey respondent is recorded as a HEART value. Thus, the HEART variable that numerically ranges from zero to a maximum of 5 indicates the severity of each respondent's heart condition.

Also shown in Table 3.4, the weighted proportion of HEART shows that 65% of the Medicare population did not suffer from any of the five above-mentioned heart diseases. In contrast, a large majority experienced chronic hypertension or high cholesterol at a certain point in their lives (68.72% and 60.29% respectively). Beneficiaries with diabetes had a modest presence of 30.82% in the surveyed population.

[7] Table 6.1 in the Appendix provides the original MCBS codes and survey questions of these five heart-disease indicators.

When evaluating their personal health compared to others of similar ages, 74% of Medicare beneficiaries interviewed in late 2013 rated their health as "Good", "Very good", and "Excellent". CV and DEFF statistics are in the normal range.

Table 3.4

Summary Statistics of Health-related Variables $(\mathcal{H}_i)$

Variable Label	Category/Response	Observation Frequency	Weighted Proportion	CV	DEFF
GENERAL	1: Excellent	1567	16.31%	2.8	1.5
	2: Very good	2923	29.34%	2.1	1.8
	3: Good	2957	28.74%	2.1	1.7
	4: Fair	1796	17.73%	2.7	1.6
	5: Poor*	805	7.88%	3.6	1.1
HYPERTENSION	1: Yes	6937	68.72%	1.1	2.6
	2: No*	3111	31.28%	2.1	1.9
HEART	0: No heart condition	6348	64.77%	1.1	2.2
	1: Experienced 1 heart condition	2069	20.02%	2.3	1.3
	2: Experienced 2 heart conditions	940	8.80%	4.6	2.1
	3: Experienced 3 heart conditions	440	4.07%	4.5	0.87
	4: Experienced 4 heart conditions	191	1.83%	7.8	1.1
	5: Experienced 5 heart conditions*	60	0.52%	15	1.1
CANCER	1: Yes	352	3.30%	6.0	1.2
	2: No*	9696	96.70%	0.84	21
DIABETES	1: Yes	3014	30.82%	2.2	2.2
	2: No*	7034	69.18%	1.2	3.5
CHOLESTEROL	1: Yes	5897	60.29%	1.3	2.6
	2: No*	4151	39.71%	1.8	2.1

Source. 2013 MCBS ATC Codebook (CMS, 2016) and Author's Calculations.

Doctor-Patient Relationship Characteristics. The $\boldsymbol{\mathcal{R}_i}$ matrix consists of categorical variables that measure the long-term relationships between Medicare beneficiaries and their primary doctors. Several studies emphasize on the quality and frequency of communication between the two parties to be significant determinants of patients' knowledge on drug expenditures and preferences for generic medications (Alexander et al., 2004; Shrank et al., 2006). Hence, the YEARS_SEEING, UNDERSTANDING, COMMUNICATION, and CONFIDENCE variables capture the essences of such doctor-patient relationship (Table 3.5). In addition, according to Westfall, McCabe, and Nicholas (1997), doctors tend to prescribe sample medications to themselves, their families, and regular patients whom they have close relationships with. Hence, the SAMPLES variable, which reports the frequency of Medicare patients asked or received free drug samples from their doctors, is relevant to our study and should be included in the $\boldsymbol{\mathcal{R}_i}$ matrix of the regression model.

Also in table 3.5, for the first four variables of the $\boldsymbol{\mathcal{R}_i}$ matrix, the majority of Medicare beneficiaries had high confidence in their doctors. Most agreed or strongly agreed that their doctors understood their medical histories well and communicated all available treatments. Interestingly, 42% of the surveyed population had seen the same doctor for more than 10 years, largely because Medicare is usually entitled to older citizens with more than 65 years of age. A small 30.7% of the Medicare population often or sometimes asked or received free drug samples from their doctors.

Table 3.5

Summary Statistics of Doctor-Patient Relationship Variables ($\mathcal{R}_i$)

Variable Label	Category/Response	Observation Frequency	Weighted Proportion	CV	DEFF
YEARS_SEEING	1: Less than 1 year*	872	8.89%	4.1	1.7
	2: 1 year to <3 years	1622	16.62%	3.3	2.1
	3: 3 years to <5 years	1338	13.65%	2.8	1.3
	4: 5 years to <10 years	1976	19.16%	2.5	1.5
	5: 10 years or more	4240	41.67%	1.9	2.7
UNDERSTANDING	1: Strongly Agree	4944	50.44%	1.4	2.1
	2: Agree	4760	46.03%	1.8	2.8
	3: Disagree	250	2.61%	7.4	1.5
	4: Strongly Disagree	43	0.40%	19	1.4
	5: No experience*	51	0.53%	16	1.4
COMMUNICATION	1: Strongly Agree	3818	39.35%	1.8	2.0
	2: Agree	5627	54.56%	1.6	3.2
	3: Disagree	489	5.02%	6.3	2.1
	4: Strongly Disagree	48	0.41%	15.0	0.96
	5: No experience*	66	0.65%	14.0	1.2
CONFIDENCE	1: Strongly Agree	4632	47.10%	1.6	2.2
	2: Agree	4925	47.90%	1.8	2.9
	3: Disagree	372	3.85%	6.5	1.7
	4: Strongly Disagree	59	0.58%	17.0	1.8
	5: No experience*	60	0.57%	16.0	1.4
SAMPLES	1: Often	530	5.54%	4.7	1.3
	2: Sometimes	2491	25.17%	2.7	2.5
	3: Never*	7027	69.28%	1.2	3.2

Source. 2013 MCBS ATC Codebook (CMS, 2016) and Author's Calculations.

Prescription Drug Coverage Satisfaction. The $\mathcal{C}_i$ matrix consists of categorical variables that evaluate the Medicare beneficiaries' satisfactions with their prescription

drug coverages. Several studies suggest that coverage type and cost-sharing setting significantly influence the generic substitution rate (Mott & Cline, 2002; Mott & Kreling, 1998; Tan, Men, & Donohue, 2014; Zweifel & Breyer, 1997). Unfortunately, the dataset does not provide individual-level coverage design. Instead, the AMOUNT_PAID, DRUG_LIST, and RECOMMEND variables, as detailed in Table 3.6, provide each survey respondent's satisfaction level with their overall plan, out-of-pocket cost, and formulary. Table 3.6 shows that 53.68% of Medicare beneficiaries were satisfied with their drug expenditures, while a smaller 28.17% were very satisfied. The large majority of the surveyed population were satisfied with other aspects of their prescription drug plan and willing to recommend to like-minded peers.

Table 3.6

Summary Statistics of Drug Coverage Variables $(\boldsymbol{C_i})$

Variable Label	Category/Response	Observation Frequency	Weighted Proportion	CV	DEFF
AMOUNT_PAID	1:Very Satisfied	872	28.17%	4.1	1.7
	2:Satisfied	1622	53.68%	3.3	2.1
	3:Dissatisfied	1338	11.84%	2.8	1.3
	4:Very Dissatisfied	1976	3.22%	2.5	1.5
	5:No experience*	4240	3.10%	1.9	2.7
DRUG_LIST	1:Very Satisfied	4944	28.03%	1.4	2.1
	2:Satisfied	4760	60.59%	1.8	2.8
	3:Dissatisfied	250	6.64%	7.4	1.5
	4:Very Dissatisfied	43	1.47%	19.0	1.4
	5:No experience*	51	3.27%	16.0	1.4
RECOMMEND	1: Yes	3818	88.47%	1.8	2
	2: No	5627	7.06%	1.6	3.2
	3: No experience*	489	4.47%	6.3	2.1

Source. 2013 MCBS ATC Codebook (CMS, 2016) and Author's Calculations.

Cost-awareness Characteristics. The $\mathcal{A}_i$ matrix consists of only the COST_AW variable and takes into account of individual cost-awareness with regards to prescribed medications, as shown in Table 3.7. Shrank et al. (2007) emphasize that the sensitivity to out-of-pocket expenses could induce patients to switch to cheaper generic medications. By including COST_AW, the model is able to account for unobservable effects of insurance cost-sharing settings. A small 14.6% of the surveyed population often or sometimes shopped around for the best drug prices and thus have a higher cost-awareness.

Table 3.7

Summary Statistics of Cost-Awareness Variable **($\mathcal{A}_i$)**

Variable Label	Category/Response	Observation Frequency	Weighted Proportion	CV	DEFF
COST_AW	1: Often	387	4.31%	6.2	1.7
	2: Sometimes	1001	10.32%	4.3	2.2
	3: Never*	8660	85.38%	1.0	6.1

Source. 2013 MCBS ATC Codebook (CMS, 2016) and Author's Calculations.

Advantages and Limitations

The 2013 MCBS ATC dataset has several key advantages. The researchers at the Office of Enterprise Data and Analytics, through a contract with NORC at the University of Chicago, professionally manage MCBS design and sampling procedure. Continuously carried out for more than 20 years, MCBS has well-established guidelines to provide user-friendly datasets and detailed instructions to researchers. With more than 10,000 survey entries, the MCBS dataset allows sophisticated statistical analyses on a nationally representative sample of the Medicare population. More importantly, because CMS recently made MCBS data publicly available, more relevant policy research on "health

disparities, access to, and satisfaction with Medicare services" can be performed (CMS, 2016). This study thus contributes to a growing literature of healthcare research based on the MCBS data.

With regards to limitations, all variables in the 2013 MCBS ATC dataset are categorical because CMS grouped interview responses into pre-defined rankings and categories. As the result, several important characteristics of the Medicare beneficiaries cannot be fully captured in the proposed model. For example, the D_INCOME variable only provides the weighted proportion of beneficiaries that earned more than $25,000 last year. It cannot be used to validate that females earning more than $100,000 a year have stronger preferences for generic medications (Shrank et al., 2009). Although the official CMS codebook and user guide help to clarify the survey questions and responses, the lack of references and related literature can cause misinterpretations of variables' meanings.

Another limitation of the 2013 MCBS ATC dataset can occur during the consolidation and selection of relevant variables. Less than 10% of the coded variables are included in the model. For instance, variables that flag recently-occurred health conditions are discarded because of strong correlations with selected variables that flag ever-occurred health conditions. In this case, the included variables might not capture the complexities of Medicare beneficiaries' medical conditions and produce inaccurate population estimates. Lastly, the list-wise elimination of survey entries with missing, "Refused", and "Don't Know" responses can also distort the sampling clusters and negatively skew relevant statistical calculations.

This section presents a detailed description of the 2013 MCBS ACT dataset, selected variables, and their applications in the proposed model. Several advantages and limitations are also thoroughly discussed to inform readers of potential pitfalls. The following section will outline the statistical results, interpretations, and econometric errors in comparison to previous studies.

Results

This section presents the results of the logistic regression model that explains the likelihood of Medicare beneficiaries requesting generic medications from their doctors. Further diagnostic tests and modifications to the preliminary model are implemented to achieve the final model. Overall, it produces significant results and explains well the relationship between requesting generics and several key characteristics of the Medicare beneficiaries including race/ethnicity, education, chronic condition status, and satisfaction with their drug coverage. Limitations concerning regression assumptions and estimation biases are addressed and indicate areas for further research.

The econometric model includes 21 explanatory variables that contribute to the likelihood of Medicare beneficiaries asking their primary doctors for generic medications. Based on previous studies on consumers' perceptions of generic medications, these variables represent testable hypotheses that involve the five primary sets of beneficiaries' characteristics. They are demographic, health status, doctor-patient relationship, insurance coverage, and cost-awareness. Table 4.1 details these hypotheses and the expected results of relevant variables.

Table 4.1

Summary of Testable Hypotheses

Group (Matrix)	Variable	Hypotheses
Demographics $(\boldsymbol{\mathcal{D}_i})$	SEX ETHNICITY_AGE INCOME EDUCATION MARRIAGE METROPOLITAN	• Females have a stronger preference for generic drugs, especially those of child-bearing age. • Beneficiaries over 55 years old with more medication experiences are more likely to switch to generics. • Beneficiaries of non-white race and inadequate health literacy are less likely to request generics due to negative beliefs. • Beneficiaries living in non-metropolitan areas or having less annual income are more likely to ask for low-cost generic medications.
Health Status $(\boldsymbol{\mathcal{H}_i})$	GENERAL HYPERTENSION HEART CANCER DIABETES CHOLESTEROL	• Beneficiaries with hypertension and other heart-related conditions are anxious about generic medications and less likely to request them. Beneficiaries with cancer and other acute conditions display similar attitude. • Recent studies argue that patients with chronic conditions experience more generic refills and tend to request them regularly.
Doctor-Patient Relationship $(\boldsymbol{\mathcal{R}_i})$	YEARS_SEEING UNDERSTANDING COMMUNICATION CONFIDENCE SAMPLES	• The first four variables are expected to be statistically significant, because they represent different aspects of the doctor-patient relationship that contribute to patient's confidences in generic medications.

		• For beneficiaries with previous experiences with drug samples, their close-knit relationship with their primary doctors can lead to a higher confidence and likelihood to request generics.
Insurance Coverage ($\boldsymbol{\mathcal{C}_i}$)	AMOUNT_PAID DRUG_LIST RECOMMEND	• All variables related to the beneficiaries' satisfactions with their drug coverages should be statistically significant and positive related to the dependent variable ASK_GENERIC. Insurance plan designs and cost-sharing settings play an important role on beneficiaries' preferences for generic medications.
Cost-awareness ($\boldsymbol{\mathcal{A}_i}$)	COST_AW	• The sensitivity to out-of-pocket drug expenditures should be statistically significant and positive related to beneficiaries' tendencies to request generics.

Preliminary Model and Evaluation[8]

Table 4.2 details the Rao-Scott Chi-Square statistics that determine the statistical significance of the preliminary model's explanatory variables. Out of these 21 variables, the model includes 16 that have significant bivariate associations with the dependent variable ASK_GENERIC. The five eliminated variables contradict with the results of previous studies and reflect the uneven distribution of the respondents who requested generics. For instance, the residences of Medicare beneficiaries (METROPOLITAN) did not significantly affect their tendency to request generics. The self-reported health assessment (GENERAL) and whether the respondent had ever had cancer (CANCER) did not correlate with their preferences for generic medications in 2013. Interestingly, the number of years that the beneficiaries had seen their primary doctors (YEARS_SEEING) and the quality of doctor-patient communications (COMMUNICATION) did not show significant associations with the likelihood that the beneficiaries would request generics. The results of these Rao-Scott tests reflect the small variability in the preferences for generic drugs among the respondents who mostly lived in metropolitan areas, were in good health, or had a long-term relationship with their primary doctors.

Table 4.2

Summary of Rao-Scott Chi-Square Statistics

Variable	Rao-Scott F-test Statistic	
SEX	F (1, 99) = 4.1519	p = 0.044
ETHNICTY_AGE	F (9.98, 988.31) = 9.0743	p < 0.001

[8] The statistical modelling and inference in this study account for the complex design and multiple sampling procedures of the 2013 MCBS ATC dataset. Heeringa, West and Berglund (2010) suggest the four stages to construct a generalized linear model for a binary dependent survey variable such as ASK_GENERIC. Most of the previous studies on MCBS-related datasets outline their methodologies in similar stages with research-specific adjustments (Henning-Smith, O'Connor, Casey, & Moscovice, 2016; Na et al., 2017; Peppone et al., 2013; Wiener, Shen, & Sambamoorthi, 2016).

INCOME	F(1, 99) = 29.0783	p < 0.001
EDUCATION	F(1.95, 193.33) = 22.7286	p < 0.001
MARRIAGE	F(2.74, 271.69) = 19.8628	p < 0.001
METROPOLITAN	F(1, 99) = 0.2236	p = 0.637
GENERAL	F(3.90, 386.56) = 0.6273	p = 0.639
HYPERTENSION	F(1, 99) = 8.0866	p = 0.005
HEART	F(4.71, 465.94) = 3.8136	p = 0.003
CANCER	F(1, 99) = 0.0204	p = 0.887
DIABETES	F(1, 99) = 16.2537	p < 0.001
CHOLESTEROL	F(1, 99) = 28.103	p < 0.001
YEARS_SEEING	F(3.79, 375.36) = 0.5309	p = 0.704
UNDERSTANDING	F(3.54, 350.26) = 2.2492	p = 0.072
COMMUNICATION	F(3.82, 377.70) = 1.1905	p = 0.315
CONFIDENCE	F(3.78, 374.16) = 2.0524	p = 0.091
SAMPLES	F(1.93, 191.10) = 170.9855	p < 0.001
AMOUNT_PAID	F(3.60, 356.05) = 49.536	p < 0.001
DRUG_LIST	F(3.85, 381.13) = 28.7723	p < 0.001
RECOMMEND	F(1.99, 197.29) = 13.5671	p < 0.001
COST_AW	F(1.98, 195.58) = 185.6958	p < 0.001

Source. Author's Calculations.

Note. Boldfaced variables are statistically significant at 10% (Heeringa et al., 2010).

After the Rao-Scott tests for model specification, the preliminary model incorporates the 16 significant explanatory variables, as boldfaced in Table 4.2, in a multivariate logistic regression and undergoes two further evaluations to ensure robustness. Firstly, the Archer-Lemeshow design-adjusted F-statistic[9] that evaluates the goodness of fit of the preliminary model is equal to 0.95 with a p-value of 0.485. Such result indicates failure to reject the null hypothesis that the preliminary model suffers from specification errors, which is not very conclusive (Heeringa et al., 2010).

Secondly, Table 4.3 details the results of the Wald-type Likelihood Ratio tests that evaluate the statistical significance of the logistic regression parameters. Several variables including SEX, INCOME, HEART, DIABETES, UNDERSTANDING, and RECOMMEND are dropped from further consideration because their associated design-adjusted Wald tests fail to reject the null hypothesis of no significance. Contrary to several studies on patients' perceptions of generic medications, sex and income of these MCBS respondents did not show significant association with their tendencies to request generics. Such result might be due to the limited number of response categories and the uneven distribution of respondents. For instance, the INCOME variable only accounts for two income bands of above and below $25,000, and close to 60% of the respondents belong to the upper band.

The severity of heart-related conditions and diabetes status also did not statistically influence the Medicare beneficiaries' tendencies to ask their primary doctors for generics. As detailed in the previous section, the construction of the HEART variable incorporates five self-selected heart-related disease indicators. Hence, selection errors

[9] Archer, Lemeshow, and Hosmer (2007) extended the standard Hosmer-Lemeshow goodness-of-fit test that can be applied to complex survey data. The Stata command *svylogitgof* was used to implement the test.

and other pre-analysis data-processing steps could possibly affect their statistical significances. The UNDERSTANDING and RECOMMEND variables might be highly correlated with other variables in the model that explain the doctor-patient relationship and beneficiaries' satisfactions with their drug coverages. Such correlations might inflate their estimators' variances and cause them to fail their respective Wald tests.

Table 4.3

Summary of Design-Adjusted Wald test Results[10]

Variable	F-Test Statistic	
SEX	F(1, 99) = 0.72	p = 0.397
ETHNICTY_AGE	F(13, 87) = 5.93	p < 0.001
INCOME	F(1, 99) = 1.13	p = 0.291
EDUCATION	F(2, 98) = 5.99	p = 0.004
MARRIAGE	F(3, 97) = 8.83	p < 0.001
HYPERTENSION	F(1, 99) = 2.84	p = 0.095
HEART	F(4, 96) = 0.87	p = 0.483
DIABETES	F(1, 99) = 0.90	p = 0.344
CHOLESTEROL	F(1, 99) = 6.64	p = 0.011
UNDERSTANDING	F(4, 96) = 1.38	p = 0.245
CONFIDENCE	F(4, 96) = 2.06	p = 0.092
SAMPLES	F(2, 98) = 67.36	p < 0.001
AMOUNT_PAID	F(4, 96) = 12.09	p < 0.001
DRUG_LIST	F(4, 96) = 5.78	p < 0.001
RECOMMEND	F(2, 98) = 1.47	p = 0.234
COST_AW	F(2, 98) = 104.80	p < 0.001

Source. Author's Calculations.

Note. Boldfaced variables are statistically significant at 10% (Heeringa et al., 2010).

[10] The null hypothesis is defined as H_0: $\beta_j = 0$ for a single parameter and H_0: $\beta_q = 0$ for q parameters. The test results are compared to the recommended significance threshold of 0.1 which decreases from that of 0.25 during the model specification stage. Such reduction allows the Wald tests to effectively detect insignificant variables and improve the model's robustness.

Final Model and Evaluation

The final logistic regression model includes the 10 statistically significant explanatory variables, as boldfaced in Table 4.3, and undergoes two similar robustness checks that applied to the preliminary model. The design-adjusted Archer-Lemeshow F-test provides evidence to suggest that the final model provides a better fit to the data than the preliminary model. Also, the Wald multi-parameter test statistic is 25.2 with a p-value less than 0.001, which provides strong evidence to reject the null hypothesis that none of the independent variables have predictive power.

Table 4.4 presents the regression results of all variables and their response categories. Statistically significant categories are boldfaced accordingly. Similar to previous MCBS-related studies, the following regression estimates are reported for each explanatory category: odds ratio (OR), standard error (SE), 95% confidence interval (CI), t-value, and p-value. According to Heeringa et al. (2010), the odds ratio "quantifies the association between the levels of a response variable and a categorical factor" more effectively in survey analyses. Specifically, it compares the odds that ASK_GENERIC takes the binary value of 1 across other levels of the explanatory dummy variable. If ASK_GENERIC is truly independent of any categorical factor, the odds ratio is equal to 1.0.

Table 4.4

Results of the Final Model

Variable	Category: Response	OR	SE	t		95% CI
constant		0.04	0.020	-6.71	p < 0.001	(0.016, 0.106)
ETHNICTY_AGE	1: Non-Hispanic White, <65 years	1.14	0.181	0.81	p = 0.420	(0.829, 1.561)
	2: Non-Hispanic White, 65-74 years	***1.29**	0.187	1.77	p = 0.080	(0.969, 1.723)
	3: Non-Hispanic White, 75-84 years	1.13	0.174	0.77	p = 0.444	(0.829, 1.530)
	4: Non-Hispanic White, 85+ years	0.98	0.148	-0.14	p = 0.889	(0.725, 1.322)
	5: Non-Hispanic Black, <65 years	***0.67**	0.147	-1.81	p = 0.074	(0.437, 1.039)
	6: Non-Hispanic Black, 65-74 years	****0.59**	0.135	-2.31	p = 0.023	(0.375, 0.928)
	7: Non-Hispanic Black, 75-84 years	*****0.43**	0.099	-3.66	p < 0.001	(0.273, 0.681)
	8: Non-Hispanic Black, 85+ years	****0.48**	0.143	-2.46	p = 0.016	(0.268, 0.869)
	9: Hispanic, <65 years	0.96	0.262	-0.16	p = 0.876	(0.556, 1.650)
	10: Hispanic, 65-74 years	0.84	0.147	-1.00	p = 0.319	(0.592, 1.188)
	11: Hispanic, 75+ years	0.91	0.172	-0.50	p = 0.620	(0.626, 1.325)
	12: Other, <65 years	0.87	0.271	-0.44	p = 0.661	(0.471, 1.616)
	13: Other, 65-74 years	0.97	0.227	-0.15	p = 0.880	(0.605, 1.539)
	14: Other, 75+ years			Reference Category		
EDUCATION	1: Less than high school			Reference Category		
	2: High school or vocational, technical, business	*****1.21**	0.075	3.10	p = 0.003	(1.072, 1.371)
	3: More than high school	*****1.25**	0.086	3.19	p = 0.002	(1.086, 1.427)

MARRIAGE	**1: Married**	***1.19**	0.120	1.71	p = 0.091	(0.972, 1.454)
	2: Widowed	0.89	0.108	-0.94	p = 0.347	(0.701, 1.135)
	3: Divorced	0.96	0.110	-0.35	p = 0.724	(0.765, 1.206)
	4: Never married			Reference Category		
HYPERTENSION	**1: Yes**	****1.14**	0.075	2.01	p = 0.047	(1.002, 1.299)
	2: No					
CHOLESTEROL	**1: Yes**	*****1.17**	0.064	2.91	p = 0.004	(1.052, 1.305)
	2: No			Reference Category		
CONFIDENCE	1: Strongly Agree	1.65	0.690	1.20	p = 0.234	(0.719, 3.784)
	2: Agree	1.71	0.715	1.28	p = 0.203	(0.745, 3.919)
	3: Disagree	1.81	0.769	1.39	p = 0.166	(0.778, 4.206)
	4: Strongly Disagree	1.33	0.732	0.52	p = 0.601	(0.449, 3.964)
	5: No experience			Reference Category		
SAMPLES	**1: Often**	*****3.83**	0.509	10.10	p < 0.001	(2.942, 4.986)
	2: Sometimes	*****1.79**	0.116	8.95	p < 0.001	(1.570, 2.031)
	3: Never			Reference Category		
AMOUNT_PAID	**1: Very Satisfied**	*****1.69**	0.286	3.08	p = 0.003	(1.204, 2.359)
	2: Satisfied	*****2.08**	0.362	4.22	p < 0.001	(1.476, 2.941)
	3: Dissatisfied	*****3.02**	0.568	5.88	p < 0.001	(2.081, 4.389)
	4: Very Dissatisfied	*****3.13**	0.733	4.86	p < 0.001	(1.963, 4.979)
	5: No experience			Reference Category		

DRUG_LIST	**1: Very Satisfied**	***2.46**	0.473	4.67	p < 0.001	(1.676, 3.600)
	2: Satisfied	***2.54**	0.468	5.08	p < 0.001	(1.766, 3.663)
	3: Dissatisfied	***2.40**	0.476	4.41	p < 0.001	(1.618, 3.554)
	4: Very Dissatisfied	***1.80**	0.506	2.10	p = 0.038	(1.032, 3.146)
	5:No experience			Reference Category		
COST_AW	**1: Often**	***4.51**	0.731	9.29	p < 0.001	(3.268, 6.221)
	2: Sometimes	***2.40**	0.211	9.94	p < 0.001	(2.015, 2.858)
	3: Never			Reference Category		

Notes. n = 33,887,711. Adjusted Archer-Lemeshow test: F(9, 91) = 1.03, p < 0.426.
Adjusted Wald multi-parameter test: F(36, 99) = 25.2, p < 0.001.
* significant at 10%; ** significant at 5%; *** significant at 1%.
Source. Author's Calculations.

Of all the demographic-related predictors, several categories of the ETHNICITY_AGE and EDUCATION variables show statistical significances. Since their associated odds ratios to request generics are less than 1.0, non-Hispanic black Medicare beneficiaries, on average, were 23% less likely to request generic medications compared with those of other demographic groups. Consistent with previous studies, these results highlight the distrust against generic medications across all age groups of African-American Medicare beneficiaries. Such distrust results from a common perception among black patients that generics are not real medicines. Sewell, Andreae, Luke, and Safford (2012) suggest that black Americans who settled for low-cost generic medications also "tied to the feelings of poor patients being at the mercy of the medical industry", which might discourage them from requesting generics. Furthermore, the results show that black beneficiaries of more than 75 years of age had the lowest odds ratios of 0.43 and 0.48, and were least likely to request generics than any other demographic group. This finding contradicts with previous studies that suggest older patients, who have more knowledge and experience about purchasing medications, are more likely to switch to available generic options (Shrank et al., 2007).

Of all the health-related explanatory variables, only HYPERTENSION and CHOLESTEROL show statistical significances. With associated odds ratios greater than 1.0, Medicare beneficiaries with chronic hypertension or high-cholesterol condition were 14% and 17% more likely to request generic prescriptions from their doctors compared with those without the conditions. These results contradict with one of the hypotheses that non-minor conditions, which are more severe than a common cold or flu, should discourage Medicare beneficiaries from consuming generics (Figueiras, Marcelino, &

Cortes, 2008; Ganther & Kreling, 2000). However, because hypertension and high-cholesterol conditions are chronic, these Medicare patients might need a large and regular supply of medications. To manage cost, Medicare sponsors and most insurance plans might require them to be on low-cost generic prescriptions for their first fills. Consequently, positive clinical outcomes, familiarity, and affordability of generic drugs could contribute to a high confidence in these Medicare beneficiaries and their tendencies to request generics for subsequent fills (Kesselheim et al., 2016).

Most of the variables that relate to the doctor-patient relationship do not show statistical significances in predicting the likelihood of Medicare beneficiaries requesting generic medications. However, the SAMPLES variable provides significant results that contribute to the existing literature. Medicare beneficiaries who often asked for or received drug samples from their primary doctors were 283% more likely to request generics than those who were unfamiliar with drug samples. In contrast, beneficiaries who occasionally asked or received drug samples were only 79% more likely to request generics than others. These results reinforce the argument that frequent encounters of generic drug samples indicate a strong doctor-patient relationship and directly promote generics consumption. As these patients become familiar with the generic treatments and receive positive outcomes from previous generic samples, they would tend to request similar generics from their primary doctors during future visits (Kesselheim et al., 2016).

All variables related to Medicare beneficiaries' satisfactions with their drug coverages show statistical significances. The AMOUNT_PAID variable indicates that beneficiaries who were very dissatisfied with their out-of-pocket drug expenditures were twice as likely to request generics compared with those who were very satisfied with such

expenses. Dissatisfactions with out-of-pocket drug costs arise when patients are charged higher co-payments or coinsurances in tiered plans. To manage these costs, these patients tended to shop around for the best drug prices and were 351% more likely to request low-cost generics compared with those who were indifferent to their drug choices and expenditures, as shown in the COST_AW variable's results. Consistent with the objectives of Medicare sponsors and insurance companies, these results indicate the success of tiered pharmacy benefit designs in steering Medicare patients toward requesting and consuming more low-cost generic medications. Given the statistical significances of drug coverage benefit design on generic drug usage, future researchers should perform more in-depth studies on specific cost-sharing settings and compare the perceptions of generics between enrollees of different Medicare plans.

These results provide the quantitative evidence of the different factors that explain the likelihood of Medicare beneficiaries requesting generics from their doctors, which carries important implications for policymakers, insurance companies, and pharmaceutical firms. Educational efforts should target demographics who were least likely to request generics, including elderly black Medicare beneficiaries and those with less education. Policymakers should clearly communicate the well-documented safety, effectiveness, and cost-saving benefit of generic medications to these beneficiaries in order to clear up negative suspicions. Previous experiences with generic drug samples also play an important role in beneficiaries' confidence in generic alternatives and their tendencies to request generics subsequently. Thus, generic pharmaceutical firms should distribute more samples and incentivize doctors to prescribe them more frequently. The generic sampling program could also dispel any negative myths coming from patients

with less medical experience or of lower socioeconomic status (S. Dunne & C. Dunne, 2016).

Understanding the importance of drug coverage design on the likelihood of Medicare beneficiaries requesting generics from their primary doctors, Medicare sponsors and private payers could pursue cost-sharing strategies that promote generics usage and help lower medication costs. Examples of such strategies include establishing tiered benefit structures that charge patients more for brand-name medications, or prior authorization programs that require patients to start with the most cost-effective generic therapies (Carlton, Bramley, Nightengale, Conner, & Zacker, 2010). Since enrollees are incentivized to shop around for the best medication prices, insurers should provide ample information on low-cost generic alternatives and ensure their availability on formularies of popular insurance plans. Resources such as GoodRx.com and Cochrane reviews should be widely accessible and inform beneficiaries of the best generic treatments with the lowest prices.

Summary

Overall, the final model supports the majority of the hypotheses listed in Table 4.1. From a total of 21 relevant variables, the final logistic regression model includes 10 variables, and the result shows statistical significances for most response categories. The reported odds ratios highlight the key characteristics of Medicare beneficiaries who tend to request generic medications from their primary doctors. Consistent with previous studies, these characteristics include race/ethnicity, age, education attainment, chronic condition status, satisfaction with drug coverage, and cost-awareness. After several robustness checks, most variables related to the beneficiaries' health statuses and relationships with their primary doctors are insignificant to the final model. However, beneficiaries with chronic hypertension, high cholesterol, or previous experiences with generics drug samples show a high likelihood of requesting generics from their primary doctors. Such findings contribute the existing literature and indicate areas for in-depth studies with different surveyed populations.

This section presents the relevant logistic regression analyses after several diagnostic tests and robustness checks. The results confirm most hypotheses about the likelihood of Medicare beneficiaries requesting generic medications. The next section will utilize the results to draw final conclusions and discuss future research.

Conclusion

According to the 2016 Annual Report of the Association for Accessible Medicines (AMA), low-cost generic medications represented over 89% of all prescriptions in the U.S. and saved consumers $1.46 trillion in the last decade. The increasing usage of generics results from an upward trend in patient knowledge and confidence toward bioequivalent medicines that can be priced as low as 2 to 10% of brand-name prices (S. Dunne & C. Dunne, 2015). For policymakers, insurance companies, and pharmaceutical firms, understanding the characteristics that drive individuals to request generics from their primary doctors is of great importance to promote generic drug usage and amplify their cost-saving benefits. The results obtained in this study could shape public education programs and future healthcare policies that make generics more accepted and requested more frequently among the general public.

The existing literature shows that physicians, pharmacists, and patients tend to have negative opinions about generic medications and their efficacies (S. Dunne & C. Dunne, 2015). In addition, most analyses involve narrowly-defined populations such as those on specific medications or culturally discrete communities (S. Dunne & C. Dunne, 2015). This study thus fills the literature gap by researching a more diverse national Medicare population and analyzing their preferences for generics. Findings from previous research help to establish the significant factors that contribute to this preference.

Based the Medicare Current Beneficiary Survey, the dataset considered in this study has the advantages of short time frame for data collection, large sample size, and cost efficiency (Cross & Kelly, 2014). As a stratified random sample of over 10,000 Medicare beneficiaries, the 2013 Access to Care dataset allows researchers to evaluate

Medicare-related policies on a national scale. Improving upon the base model by Mott and Cline (2012), the construction of the multivariate logistic regression model includes 21 relevant variables related to beneficiaries' demographics, self-reported health statuses, doctor-patient relationships, drug coverages, and cost-awareness.

Based on the final analyses of 10,048 interview entries projected to a population estimate of 33,887,711, the results provide important implications and are comparable with those of previous studies. Most demographic characteristics such as race/ethnicity, age, and education were statistically significant and reflected the anticipated odds ratios. For example, non-Hispanic black beneficiaries aged 65 and older were significantly less likely to request generics from their primary doctors compared with those of other demographics. Beneficiaries with high-school or higher levels of education also showed a high likelihood to request generics. Several discrepancies with previous findings should also be noted. Except for chronic hypertension and high cholesterol, most indicators of beneficiaries' health conditions bear no statistical significance with their tendencies to ask for generic medications. Sex, income level, and whether the Medicare beneficiaries lived in metropolitan areas also display no statistical relationship with their likelihood of requesting generics. These results reflect the uneven distribution of survey respondents and other unobservable flaws of the primary dataset.

The final model delivers significant results on variables that address critical aspects of the beneficiaries' doctor-patient relationships, drug coverages, and cost-awareness which existing literature did not discuss thoroughly. For instance, when the beneficiaries were satisfied with their out-of-pocket drug expenditures and formularies, they would be more likely to seek generic substitutions than those who were dissatisfied

with such aspects of their drug coverages. Beneficiaries who had previous experiences with generic drug samples or were price-sensitive when shopping for medications also tended to request generics. Such findings highlight the important role of insurance plan designs and cost-sharing settings in promoting generic drug usage among Medicare beneficiaries.

The applications of these results extend to public education programs and recommendations for future Medicare-related policies that can promote generic drug usage and help curb the rising healthcare cost. Educational efforts and advertising campaigns on the effectiveness and cost-saving benefits of generic medications can target certain demographics of Medicare beneficiaries who tend to distrust generics. Generic pharmaceutical firms can implement sampling programs that introduce more Medicare beneficiaries to try generic alternatives. Private insurers and Medicare sponsors can design effective cost-sharing settings and steerage programs that encourage Medicare beneficiaries to request generics more frequently and reap the enormous cost-saving benefits.

Several limitations of the primary dataset and the regression model point to areas for improvement and for future research. All findings were generalized only to the population of Medicare beneficiaries in 2013 and not to the general population at large. As a result, the model might produce drastically different inferences about other populations, and further geographical studies could identify such regional disparities (Taira et al., 2016). Given that the MCBS dataset has a cross-sectional design, the model's results simply reflect relationships between the dependent and the explanatory variables and do not necessarily imply causations (Chromy & Abeyasekera, 2005;

Henning-Smith, O'Connor, Casey, & Moscovice, 2016). In the future, researchers could investigate the changes of Medicare beneficiaries' tendency to request generics over time by combining multiple years of Medicare survey records into a longitudinal panel dataset.

All analyses in this study utilize post-stratification weights to account for the complex design of the Medicare Current Beneficiary Survey dataset and to minimize the potential effects of differential non-responses (Na et al., 2017). Yet, CMS purposely oversampled certain subpopulations to fit the organization's needs of examining all Medicare-related programs. Hence, the statistical generalizations of MCBS-sourced variables could be skewed and might not be suitable to research questions related to generic medication usage. Moreover, because this study is a secondary analysis of a MCBS dataset compiled in 2013, challenges including lack of control over survey design, population selection, and data collection limit the scope of this study and the extrapolation of statistical inferences about other demographic groups. For example, most variables related to beneficiaries' insurance coverages depend on the subjective measure of satisfaction that might be differently defined by individuals and across cultural or geographical regions (Henning-Smith, O'Connor, Casey, & Moscovice, 2016). Future researchers could investigate more interesting hypotheses and construct more accurate models of the beneficiaries' tendencies to request generics with a dataset of more specific and continuous variables such as annual income, insurance premium amount, and exact annual out-of-pocket drug expenditure.

Due to survey weights and sampling adjustments, most common regression statistics and tests are inapplicable to the primary dataset. For instance, the standard maximum likelihood estimation procedures could not be utilized in this multivariate

logistic regression model. The stratification and clustering of sample observations invalidate the assumption of observational independence that is crucial to most statistical tools used to estimate model parameters and compare alternative models (Heeringa et al., 2010). However, this study takes advantage of newly-developed research methods including the PMLE approach,[11] balanced repeated replication, Wald test, and Archer-Lemeshow goodness-of-fit test to ensure the proposed model's robustness. Since applied survey data analysis is still in its developing phase and increasingly integrated into statistical software, future researchers will be equipped with more advanced techniques and capable to build better regression models that capture the likelihood of Medicare beneficiaries requesting generics.

Overall, this study is an important addition to the literature on generic medication usage because it focuses on patients' positive perceptions of generics. The implemented model ably explains the likelihood that Medicare beneficiaries request generics from their primary doctors and produces significant results that align with most previous findings. Future researchers can utilize this econometric model for in-depth studies related to generic drug usage and analyze the perceptions by other populations outside the Medicare program and the U.S. Given the implications of the results in this study, policymakers, Medicare sponsors, insurance companies, and generic drug manufacturers could pursue effective healthcare policies and marketing strategies that promote generics usage and potentially save patients billions of dollars in medication expenditures.

[11] PMLE stands for pseudo-maximum likelihood estimation that was proposed by Binder (1983).

APPENDIX

Table 6.1

Summary of the Original MCBS Codes and Survey Questions

Variable Label	MCBS Code	Survey Question/Description
SEX	IV_AGE	Recode of administrative data on age
ETHNICTY_AGE	D_RE_AGE	Recode of reported race and ethnicity information and administrative data on age
INCOME	D_INCOME	Was [your and your spouse's/(SP's) and (his/her) spouse's/[your/(SP's)]] total income during the past 12 months less than $25,000 or $25,000 or more, before taxes? Include income from jobs, Social Security, Railroad Retirement, other retirement income, Supplemental Security Income (SSI), pensions, interest, and any other sources.
EDUCATION	D_EDU	What is the highest degree or level of school [you have/(SP) has] completed?
MARRIAGE	D_MARSTA	[Are you/Is (SP)/Was (SP)/Is (SP) currently/Are you currently] married, widowed, divorced, separated, or never married?
METROPOLITAN	ADM_H_METRO	Recode of administrative data on metro status
GENERAL	HLT_GENHELTH	Now, I would like to ask you about [your/(SP's)] health. In general, compared to other people [your/(SP's)] age, would you say that (your/his/her) health is…?

HYPERTENSION	HLT_OCHBP	[[Since (LAST MONTH YEAR) has/Has] a doctor (ever) told [you/(SP)] that (you/he/she) (still have/still has/have/had)...] hypertension, sometimes called high blood pressure?
HEART	HLT_OCMYOCAR	[[Since (LAST MONTH YEAR) has/Has] a doctor (ever) told [you/(SP)] that (you/he/she) had...] a myocardial infarction or heart attack?
	HLT_OCCHD	[[Since (LAST MONTH YEAR) has/Has] a doctor (ever) told [you/(SP)] that (you/he/she) had...] angina pectoris or coronary heart disease?
	HLT_OCCFAIL	[[Since (LAST MONTH YEAR) has/Has] a doctor (ever) told [you/(SP)] that (you/he/she) had...] congestive heart failure?
	HLT_OCCVALVE	[[Since (LAST MONTH YEAR) has/Has] a doctor (ever) told [you/(SP)] that (you/he/she) had...] problems with the valves of the heart, such as aortic stenosis?
	HLT_OCRHYTHM	[[Since (LAST MONTH YEAR) has/Has] a doctor (ever) told [you/(SP)] that (you/he/she) had...] problems with the rhythm of (your/his/her) heartbeat, such as atrial fibrillation?
CANCER	HLT_CANCER	Since (LAST MONTH YEAR), did a doctor tell [you/(SP)] that (you/he/she) had any kind of cancer, malignancy, or tumor other than skin cancer?
DIABETES	HLT_OCBETES	Has a doctor ever told [you/(SP)] that (you/he/she) had any type of diabetes, including: sugar diabetes, high blood sugar, (borderline diabetes, pre-diabetes, or pregnancy-related diabetes/borderline diabetes, or pre-diabetes)?
CHOLESTEROL	HLT_OCCHOLES	Has a doctor ever told [you/(SP)] that (you/he/she) had high cholesterol?

YEARS_SEEING	ACC_USHOWLNG	How long [have you/has (SP)] been [seeing (PROVIDER NAME)/going to (PROVIDER NAME)]?
UNDERSTANDING	ACC_USUNHIST	[[Your/(SP's)] doctor has/The doctors at (PROVIDER NAME) have] a good understanding of (your/his/her) medical history.
COMMUNICATION	ACC_USTELALL	[[Your/(SP's)] doctor tells/The doctors tell] (you/him/her) all (you want/he wants/she wants) to know about (your/his/her) condition and treatment.
SAMPLES	ACC_SAMPLERX	Please tell me how often during (CURRENT YEAR) [you have /(SP) has] done any of the following things. [Have you/has (SP)] often, sometimes, or never asked for or received free samples from (your/his/her) doctor or health provider?
AMOUNT_PAID	ACC_MCAMTPAY	[Please tell me how satisfied you have been with . . .] The amount [you have/(SP) has] to pay for [your/(SP's)] prescribed medicines.
DRUG_LIST	ACC_MCDRGLST	[Please tell me how satisfied you have been with . . .] [Your/(SP's)] prescription drug plan's formulary or the list of drugs covered by the plan.
RECOMMEND	ACC_MCRECPLN	Would [you/(SP)] recommend (your/his/her) prescription drug plan to other people like (you/him/her)?
COST_AW	ACC_COMPARRX	Please tell me how often during (CURRENT YEAR) [you have /(SP) has] done any of the following things. [Have you/has (SP)] often, sometimes, or never compared prices or shopped around for the best prices?

Source. 2013 MCBS ATC Codebook (CMS, 2016).

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